

A NEW APPROACH FOR DIAGNOSING EPILEPSY BY USING WAVELET TRANSFORM AND NEURAL NETWORKS

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Abstract: Today, epilepsy keeps its importance as a major brain disorder. However, although some devices such as magnetic resonance (MR), brain tomography (BT) are used to diagnose the structural disorders of brain, for observing some special illnesses especially such as epilepsy, EEG is routinely used for observing the epileptic seizures, in neurology clinics. In our study, we aimed to classify the EEG signals and diagnose the epileptic seizures directly by using wavelet transform and an artificial neural network model.

EEG signals are separated into δ , θ , α , and β spectral components by using wavelet transform. These spectral components are applied to the inputs of the neural network. Then, neural network is trained to give three outputs to signify the health situation of the patients

Keywords: wavelet, neural network, epilepsy, EEG

I. INTRODUCTION

In medicine, EEG keeps its importance for identifying the physiological, and the psychological situations of the human and the functional activity of the brain. In neurology clinics EEG device is used efficiently for observing the brain disorders.

According to the spectral components, and the amplitudes of these spectral components, which EEG consists, different interpretations can be made about the recorded waveform (the patient is healthy or not). The most important frequency component of the human's EEG is α wave (approximately between 8-12Hz), and α wave is sometimes called as the natural frequency of the brain (1). This wave appears when the eyes are closed and one begins to rest. In epilepsy cases, however, when the epileptic seizures occurs, δ , θ waves, which have lower frequencies, and higher magnitudes with respect to α waves, should be seen (δ , θ waves has 0-4Hz, 4-8Hz frequency ranges, respectively). In addition, brain produces desynchronize waves, which have higher frequency, lower magnitude, called β waves (frequency range is higher than 13Hz). Therefore, for diagnosing the brain disorders, these spectral components must be analyzed carefully.

When the EEG waveform is observed, it is seen that EEG waveform is a non-stationary signal. For this reason, when the frequency components of the EEG is extracted by using the Short Time Fourier Transform (STFT) and the wavelet transform, including stft, should be useful than the other spectrum analyzing methods (AR, ARMA, FFT etc).

Furthermore, viewing the results of the wavelet transform in time domain should be useful to make additional comments.

After these processes, if we think that the person who diagnoses the illnesses is a doctor, use of an artificial neural network (ANN) should be offered. Because, by using the artificial neural network should minimize the errors done by doctors when they diagnose the illness

In our study, EEG data sets are collected by a system, which has been used in our previous studies. From the EEG data sets, obtained δ , θ , α , and β waves are extracted by using wavelet transform. After all, according to these waves an artificial neural network trained, and developed to diagnose the epileptic cases.

II. MATERIALS AND METHODS

A. Obtaining The EEG Data Sets

In our previous studies, a data accusation and processing unit (PCI-MIO-16-E4) is used to record the EEG data to make computer-based analysis. Recordings have been made as 202 samples during 6 seconds. The accusation unit has a 12 bits analog to digital converter (AD 7572, % 0.02 sensitivity, 0.014ms conversion time) to discretize the EEG waveform. The EEG recording unit is shown in fig. 1.

B. Wavelet Transform

If a signal does not change much over time, we would call it as a stationary signal. Fourier transform could be applied to the stationary signals easily and good result can be taken. However, like EEG, a plenty of signals contain non-stationary or transitory characteristics, and Fourier Transform is not suited properly to detect the non-stationary signals.

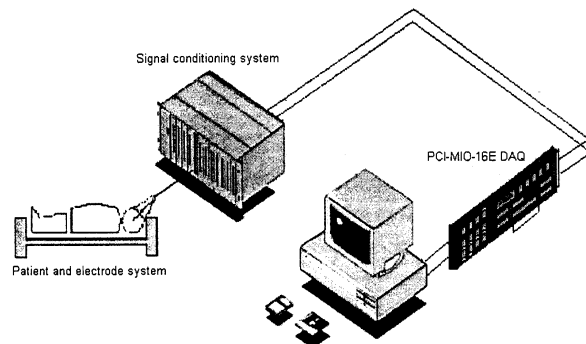


Fig. 1. Data acquisition system

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In an effort to correct this deficiency, Dennis Gabor (1946) adapted the Fourier transform to analyze only a small section of the signal at a time, which is called as Short Time Fourier Transform. One of the major features of stft is mapping the signal in two-dimensional function of time and frequency.

The Wavelet Transform decomposes a signal onto a set of basic functions called wavelets. These basic functions are obtained by dilations, contractions and shifts of a unique function called the wavelet prototype. In order to the input signal $x(t)$, Wavelet Transform should be separated as Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). We can identify the CWT as in (1);

$$\text{CWT}(a,b)=\int x(t).\Psi_{a,b}^*(t).dt \quad (1)$$

where $*$ denotes the complex conjugate, $a \in \mathbb{R}^+$ represents the scale parameter, $b \in \mathbb{R}^+$ represents the translation, and $\Psi_{a,b}(t)$ is obtained by scaling the prototype wavelet $\Psi(t)$ at a time b , and scale a as in (2);

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}} \Psi\left(\frac{t-b}{a}\right) \quad (2)$$

Generally in wavelet applications, orthogonal dyadic functions are chosen as the mother wavelet. This transform is often discretized in a and b on a dyadic grid with the time remaining continuous. The mother wavelet, commonly used, is (3);

$$\Psi_{j,k}(t) = 2^{-j/2} \Psi(2^{-j}t - k) \quad (3)$$

where $\{\Psi_{j,k}(t), j, k \in \mathbb{Z}\}$ for $L^2(\mathbb{R})$

C. Artificial Neural Network

Neural networks are used as a powerful means in engineering area after the development especially, in computer technology. The fundamental characteristic of the neural networks is an adaptive, non-algorithmic and parallel-distributed memory [1].

Artificial neural networks are modeled by inspiring from biological neural system and have a more simple structure. Many neural networks were developed for resembling several known characteristics of biological neural networks such as learning and reacting. Some characteristics, however, are realized with an engineering approach instead of neuropsychological one [2].

III. EXPERIMENTAL STUDY

In this study, first EEG waveforms have been recorded by a data acquisition and processing unit. One of the recorded EEG waveform is shown below. Then, the wavelet transforms of the recorded EEG waveforms are taken by using daubechies wavelets. Recorded EEG waveforms are

first divided into low and high wavelet coefficients, and these low and high wavelet coefficients are divided in to their sub-high and sub low coefficients. Therefore, δ , θ , α , and β wavelets of the original EEG waveform are obtained.

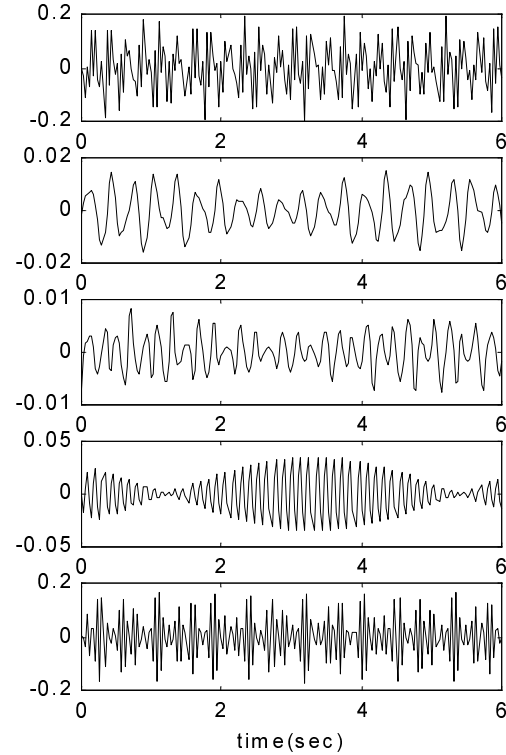


Fig. 2. Simulated EEG waveform and its spectral components due to wavelet transform

The results of Wavelet Transform of the different EEG's are shown in figure 2, 3, and 4.

In these figures first the EEG waveform has been given. Then the sub-spectral components depending each EEG are given. The δ , θ , α , and β waves are viewed in the figure by the following windows. And figures 2,3,4 show the EEG waveforms as simulation, healthy and epileptic respectively.

Classification is based on the partition of every section of the space formed by EEG wavelet signals and determination of a partitioning function related with those sections; in case of the ignorance of the mathematical forms of the partitioning functions, first a learning activity should be realized. Learning activity provides the determination of the real values of these functions with the aid of the examples from every class (training set) [3]. Since the classifiers are based on deciding by learning, they lead to more successful results with respect to the traditional (non-learning) methods [4].

Back propagation network is a multi-layer feed forward networks. It is an artificial neural network between the input and an output layer, of which more than one layer is used. In these immediate layers called as hidden layer, there are processing elements, which don't receive input and give

output without any means. The general layout of a multi-layer neural network classifier, shown in fig. 5. is given [5].

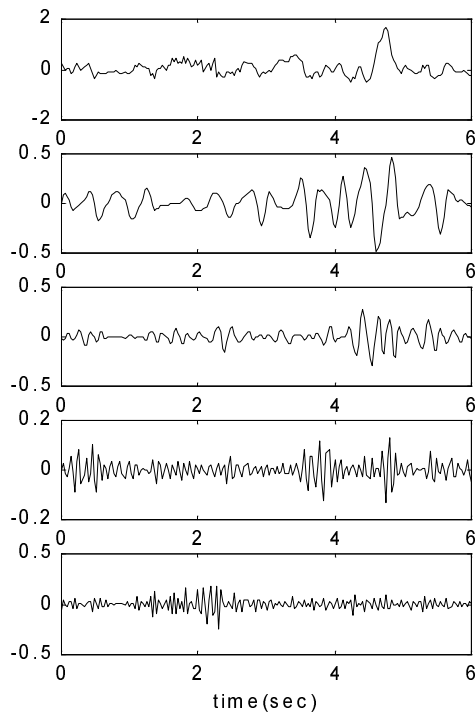


Fig. 3. Epileptic EEG waveform and its spectral components due to wavelet transform

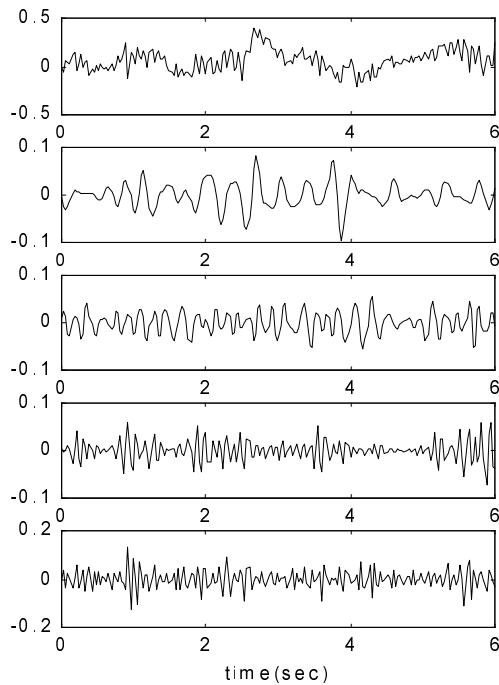


Fig. 4. Normal EEG waveform and its spectral components due to wavelet transform

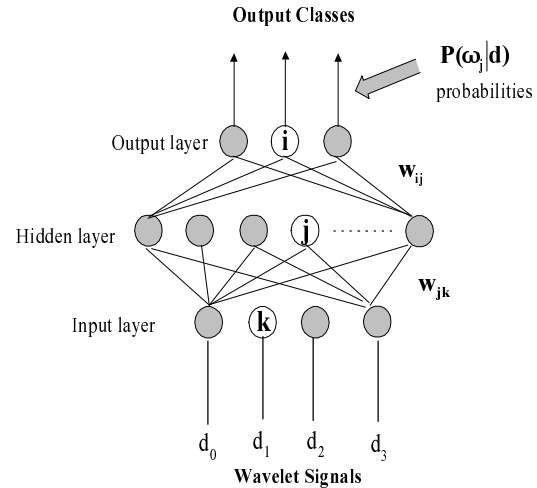


Fig.5. Multi layer feed forward neural network classifier.

Then the training characteristics of neural network used in this study are as follows;

Structure:

Layer number: 3

The number of neuron on the layers: (4x202) - 15 -3

Training Parameters:

Adaptive learning coefficient: 0.0005

Momentum coefficient: 0.95

Sum-squared error-sse: 0.0005

Activation Function: tangent sigmoid

The variation of system error in according to the learning iteration during the training stage of back propagation network is given in fig. 5. There is not any instability or roughness in training process of the network. This shows the convenience of the parameters chosen to train the networks.

In the second stage, the trained network was tested with EEG wavelet signals. As a result it was seen that by observing the output vector produced by the network it was possible to diagnose the disease.

Finally several types of EEG recordings that we have used in the study have tested the developed network. And the responses of the network to these test signals are shown in table 1.

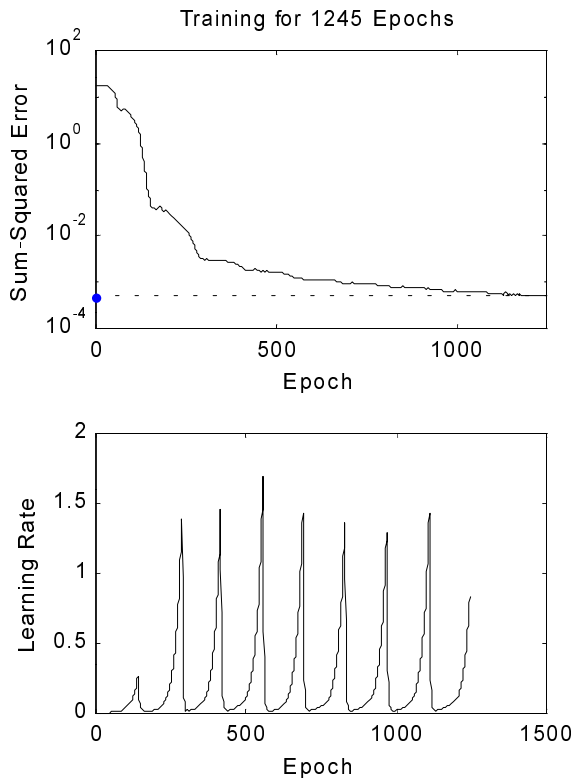


Fig. 6. s.s.e and learning rate versus iteration number

Table 1. Result of the test signals

Signals	Diagnosis	Recognition Rate (%)
Test signal 1	Epileptic	97
Test signal 2	Healthy	95
Test signal 3	Healthy	98
Test signal 4	Healthy	97
Test signal 5	Healthy	95
Test signal 6	Pathologic	93

IV. CONCLUSION

In our study, we have tried to find a new solution for diagnosing the epilepsy. For this aim, the Wavelet Transform of the EEG signals have taken, and the δ , θ , α , and β sub-frequencies are extracted. Depending on these sub-frequencies an artificial neural network has been developed and trained. The accuracy of the neural network outputs is too high (%97 for epileptic case, %98 for healthy case, and % 93 for pathologic case that have been tested). This means that this neural network identifies the health conditions of the patients approximately as 90 of 100. From this point we can say that an application of this theoretical study will be helpful for the neurologists when they diagnose the epilepsy.

Furthermore we want to develop the practical application of this study. After all a small model of this system will be very useful for the patients suffer from epilepsy.

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